Application Of Machine Learning Techniques To Predict Soaked CBR Of Remolded Soils

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Abstract

The machine learning techniques such as Artificial Neutral Network (ANN) have better predicting capability and have found wide application in geotechnical engineering. The soil strength indicator CBR could be predicted from other soil characterizing parameters with the aid of ANN methods. Such an attempt, with the aid of large input-output data base has been presented in this paper. The two ANN methods namely General Regression Neural Network (GRNN) and Multilayer Perceptron Neural Network (MLPN) using Levenberg-Marquardt back-propagation (LMB) algorithm neural network techniques have been used in the modeling. The data base was prepared in the laboratory by conducting tests on 60 soils. The particle size distribution, liquid and plastic limits, modified compaction test and the soaked CBR have been determined. The commercially available software MATLAB-7.5 has been used to develop ANN models. In both the models input layer containing six nodes (basic soil parameters) and the output layer containing a single node (i.e. CBR) have been taken. The strengths of the developed models have been examined in terms of regression coefficient (R^2) and mean square error (MSE) values. It is found that both GRNN and MLPN models predict CBR close to the experimental value. However, the prediction of CBR by GRNN is found better than MLPN.

Keywords CBR, Remolded soils, GRNN, MLPN

1. Introduction

Roadway pavements are an important and integral element of surface transportation infrastructure. The subgrade soil provides a foundation for supporting the pavement structure hence its properties are important input parameter in the pavement design. Usually, the California Bearing Ratio (CBR) of subgrade soil is considered as an indicator of strength and is used in the design of the pavement; hence a reliable estimation of its value is a must. In many situations soaked CBR of subgrade soils, at a definite interval of road alignment, needs to be determined. This necessitates testing of large number of soil samples. Further, where the subgrade soils are poor in certain characteristics, they may require mixing with other available soils in different proportions, so as to obtain desired quality material. These mixed soils are referred as artificial soils. Thus the testing of raw soil samples and artificial soil samples consumes a lot of time. A few repetition tests are also sometimes needed then the testing duration expands to many months and the project delays. In order to resolve this issue and to have an independent check on the test results, empirical correlations of CBR with basic soil properties could be a good choice.

Prediction of soil engineering properties from their index and state parameters is not new. Earlier empirical correlations have been developed and the compaction parameters [2], permeability [5], unconfined compressive strength ([9],[12]), angle of shearing resistance[13], shear strength ([7],[11],[16],[25]), bearing capacity [19], resilient modulus[30], of soils have been related to their physical properties such as void ratio, particle size d_{10} (size corresponding to 10% finer), % finer than 425 micron, liquid limit, plasticity index etc. The CBR is also been related to some of the physical properties ([14], [18], [27], [28], [29]). Some of the correlations, which are found in the literature, are as follows.

Black (1962) has given the graph between soil indices Plasticity Index (PI), Liquidity Index (LI) and the CBR, which is applicable for saturated clays.

Johnson and Bhatia (1969) have correlated CBR with suitability index, which is a function of plasticity and gradation of soil.

Agrawal and Ghanekar (1970) have proposed the relation in the form of an equation:

CBR = 2.0-16.0*log (OMC) +0.07*LL………. (1)

where, OMC is the standard Proctor moisture content in fraction and LL is the liquid limit value of the soil.

NCHRP (2001) has given the following two equations

$CBR = 28.09(D_{60})^{0.358}$ ………………………. (2)

For coarse grained soils, and

CBR = 75/ (1+0.728(F_2*PI)) ………..………. (3)
For plastic fine grained soils

where D_{60}=diameter of particles corresponding to 60% passing (mm) F_2 = % passing 200 US sieve (i.e. Finer than 75micron)

On critically examining the utility of such correlations, it is observed that these find limited applications as they are either developed for a particular soil type or consider the effect of only a few parameters on CBR. With the application of ANN techniques in geotechnical engineering better correlation between the soil properties can be developed then that by the linear or multiple regression methods.

The ANN models work on the principle of the biological structure of human brains and consist of an interconnected assembly of simple processing elements known as neurons, which are organized in a layered fashion. It is the large amount of interconnections between these neurons and their capability to learn from data in an adaptive environment that solve the complex non linear real world problems. The success of the techniques depends on the interconnection pattern between different layers of neurons, the learning process for updating the weights of the interconnections and the activation function that converts a neuron's weighted input to its output activation.

In the present work two ANN models namely GRNN and MLPN have been used to predict soaked CBR of a few soils from their basic soil parameters, which are more commonly and readily determinable in the laboratory. The development of ANN model requires use of large data base for training, testing and validation. This has been accomplished by conducting various tests on three natural soils and fifty seven artificial soils. The artificial soils have been obtained from the combination of natural soils mixed in different proportions. In the following paragraphs brief description of soils used, their properties determined and the process of development of ANN models have been discussed and is followed by the performance evaluation of the same.

2. Generation of data base: The natural soils used in the study are yellow soil, copra soil and the murrum (copra soil is the local name to highly weathered basalt and murrum is a mixture of coarse and fine grained red soil). The yellow soil was collected from LNCT campus, Kalchurinagar, Bhopal (India). The other two soils namely Copra and Murrum have also been taken from the nearby area. These are the soils that are commonly found in the Central part of the India.

The grain size distribution, Atterberg limits, Modified Compaction test have been performed on these soils as per relevant IS code methods. The CBR mould was prepared by mixing the soil with the moisture corresponding to its optimum value obtained in compaction test. The soaked CBR was determined by placing the moulds in water for 96 hrs prior to testing as per IS 2720 part 16. The properties of the natural soils are given in Table-1.

Table 1: Properties of Natural Soils

S. No	Soil Parameter	Yellow soil	Copra soil	Murrum soil
1	Gravel content, %	10.6	42.7	22.0
2	Sand content, %	23.4	41.9	51.04
3	Silt and clay content, %	66.0	15.4	26.96
4	Liquid Limit, LL	38	0	52
5	Plastic limit, PL	23	0	30
6	Plasticity index, PI	15	0	22
7	Soil classification	CI	GM	SM
8	Sp. Gravity	2.69	2.60	2.65
9	Optimum Moisture Content, OMC, %	15.66	11.12	12.25
10	Maximum Dry Density, MDD, g/cc	1.89	2.07	2.04
11	California Bearing Ratio, CBR (soaked)	4.17	23.49	17.69

The artificial soils were obtained by mixing copra and murrum soils to the yellow soil in different proportions varying from 5% to 95% in interval of 5% each separately. Further, the two soils copra and murrum together were also mixed to the yellow soil. Nineteen combinations of mix soils containing yellow and copra, yellow and murrum and murrum-copra- yellow each has resulted into total 57 soil types. These have been tested and all the parameters that have been determined for natural soils are obtained. The range of value of soil parameters for these mix soils is given in Table-2.

Table 2: Range of soil parameters of artificial soils

S. No	Soil Parameter	Yellow soil and Copra soil	Yellow soil and Murum soil	Murum soil and Copra soil
1	Sand content, %	25.17-41.34	24.23-52.48	51.21-42
2	Silt and clay content, %	60.46-18.07	64.75-25.74	15.7-26.4
3	Liquid Limit, LL	37-24	39-52	51-27
4	Plastic limit, PL	21-12	23-38	30-12
5	Plasticity index, PI	16-12	16-14	21-15
6	Optimum Moisture Content, OMC, %	15.32-11.07	15.62-12.51	12.2-11.2
7	Maximum Dry Density, MDD, g/cc	1.92-2.06	1.91-2.04	2.04-2.06
8	California Bearing Ratio, CBR (soaked)	5.05-23.11	4.51-17.15	17.87-23.29

3. Development of neural network models

The two different modeling options, under ANN methods namely Multilayer Layer Perceptrons Neural (MLPN) Network and General Regression Neural Network (GRNN) algorithm have been employed in the present work. A review of literature suggest that the strength of a soil depend on soil particle size distribution, type of mineral, dry density, moisture content and degree of saturation [11]. The sand content, F1 and, the silt and clay content, F2 in a soil takes into account the effect of particle size distribution. The liquid limit, LL and plasticity index, PI takes into account the influence of soil mineral. The OMC and MDD takes into account the degree of compactibility of the soil. Hence F_1, F_2, LL, PI, OMC and MDD are employed in the present work for developing models for CBR prediction. The commercially available package, MATLAB 7.5 is used to construct ANN models.

Multilayer layer perceptrons neural network

The MLPN that are trained with Levenberg-Marquardt back-propagation algorithm has been used. The multilayer perceptrons network MLPN is one of the popular network architecture in use today ([3][22],[24]). The MLPN consists of an input layer, a number of hidden layers, and an output layer. In each of the hidden layers, the number of node can be varied. Due to the number of layers and the number of nodes in each layer, the MLPN can adjust the architecture of the network based on the complexity of a problem. In MATLAB- 7.5, the MLPN has up to three hidden layers available. Each of the nodes in the network performs a biased weighted sum of their inputs and passes this activation level through a transfer function to produce its output. The weights and biases in the network are adjusted using a training algorithm. The training algorithm used is back propagation Levenberg-Marquardt. According to a universal approximation theorem a single hidden layer network is sufficient for the MLPN to uniformly approximate any nonlinear function.

Selection of number of hidden layer, number of neurons in hidden layers, learning rate moment (lr), momentum coefficient (mc), epochs and activation function type plays an important role in the model performance. In the present work herein, about 70% of the available data (42 data sets out of 60 data sets) was used for training and validation session and about 30% (18 data sets out of 60 data sets) was used for testing session. In order to obtain optimum number of hidden layer/s in Train-lm models four networks with one, two, three and four hidden layers were trained. The network with one hidden layer, lead to minimum Mean Square Error (MSE) value in comparisons with two, three and four hidden layers. The model was trained, fed neurons at minimum MSE in the hidden layer. The neural network was trained by varying learning rate moment (0.01, 0.03 and 0.05) and momentum coefficient (0.5 and 0.7) and number of optimum neurons (obtained at minimum MSE). The cross validation approach is used to determine the best network structure in this study.

In an overall sense, model was developed with single hidden layer with 42 hidden neurons, 0.03 learning rate moments and 0.7 momentum coefficients gave better performance compare to other values of m_c, and l_r. The regression coefficient (R^2) and MSE values are shown in Table 3. The results obtained from MLPN model has been compared with experimental results as shown in Fig. 1a and 1b.

Table 3: R^2 and MSE Values

Performance	Training CBR	Testing CBR
R^2	0.9701	0.7180
MSE	0.5214	3.88

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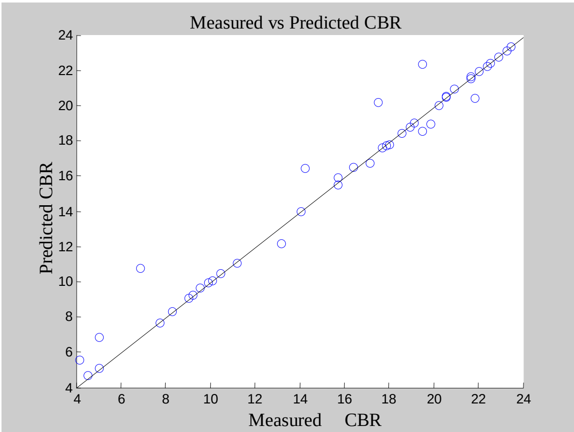

Figure 1a: Comparison of predicted and measured CBR (Training Data Set)

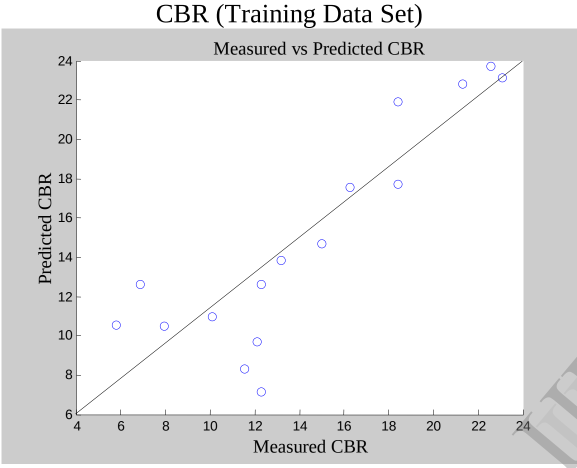

Figure 1b: Comparison of predicted and measured CBR (Testing Data Set)

General regression neural network

The general regression neural network (GRNN) is frequently used for estimating the probability density function ([17], [26]). GRNN has four layers, one input layer, two hidden layers, and one output layer. The first hidden layer consists of the radial units. These radial units represent clusters rather than each training case. The center of the clusters can be assigned using subsampling or Kohonen algorithm [15]. The number of node in the first hidden layer can be as many as the number of cases. The second hidden layer consists of units that help estimate the weighted average. The second hidden layer always has exactly one more node than the output layer. Since only one output is considered in the present study (CBR), the second hidden layer has only two nodes.

In the present study, 42 data base has been used for training and validation and 18 data base has been used for testing the network. GRNN trained with 42 nodes in the hidden layer with varying radius as 0.1, 0.3 and 0.5. The network with 0.1 radius gave best performance (maximum R^2 and minimum MSE) compare to train with other radiuses. $R^2$and MSE values are shown in Table 4. The results obtained from GRNN model have been compared with experimental results as shown in Fig. 2a and 2b

Table 4: R^2 and MSE Values

Performanc	Training	Testing
e	CBR	CBR
R^2	0.9986	0.9885
MSE	0.0212	0.2252

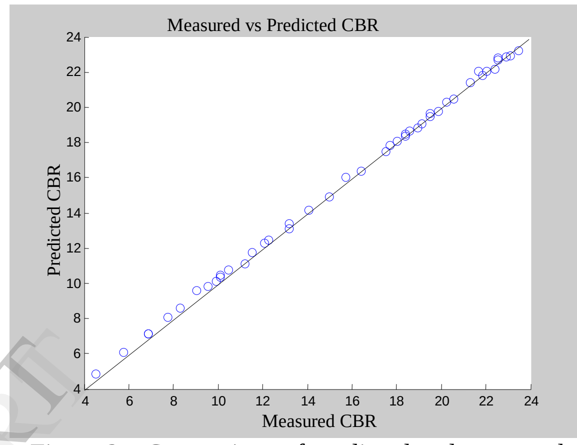

Figure 2a: Comparison of predicted and measured CBR (Training Data Set)

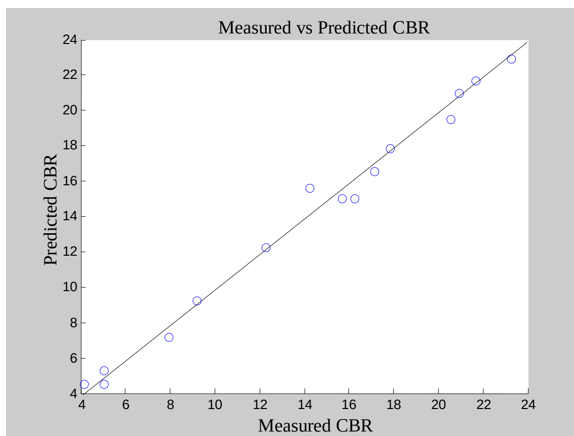

Figure 2b: Comparison of predicted and measured CBR (Testing Data Set)

From the Table 3 and Table 4 it can be deduced that both MLPN and GRNN capture neurons and gave high R^2 value during training phase. However, in testing phase GRNN perform better in terms of R^2 and MSE in comparison to MLPN.

4. Conclusions

The prediction of CBR from basic input soil properties have been attempted in the present work for the three most common natural soil types found in the central part of India. A large data base is generated by conducting tests on these soils and on artificial soils derived by mixing them in different combinations. The ANN models have been developed using MLPN and GRNN algorithms with basic soil parameters namely % of sand (F1), % of silt and clay(F2), Liquid Limit(LL), Plasticity Index (PI), Optimum Moisture Content (OMC), and Maximum Dry Density(MDD) in input layer and CBR as a single parameter in the output layer. The MLPN with varying learning rate moment (0.01, 0.03 and 0.05) and momentum coefficient (0.5 and 0.7) gives $R^2$and MSE values in training and testing phase as 0.97, 0.52 and 0.71, 3.88 respectively and could be regarded as fairly good in predicting CBR from the selected basic input soil parameters. The other model used is GRNN with varying radius (0.1 to 0.5). It gives $R^2$and MSE values in training and testing phase as 0.99, 0.02 and 0.98, 0.22 respectively and can be regarded as more refined tool then the MLPN. Thus it can be concluded that GRNN better predict CBR for remolded soils.

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